ADOPTION OF AN UNMANNED HELICOPTER FOR LOW-ALTITUDE REMOTE SENSING TO ESTIMATE YIELD AND TOTAL BIOMASS OF A RICE CROP

K. C. Swain, S. J. Thomson, H. P. W. Jayasuriya

ABSTRACT. *A radio-controlled unmanned helicopter-based low-altitude remote sensing (LARS) platform was used to acquire quality images of high spatial and temporal resolution in order to estimate yield and total biomass of a rice crop (*Oriza sativa L.*). Fifteen rice field plots with five N treatments (0, 33, 66, 99, and 132 kg ha^{-1}) having three replicates each were arranged in a randomized complete block design for estimating yield and biomass as a function of applied N. Images were obtained by image acquisition sensors mounted on the LARS platform operating at the height of 20 m over experimental plots. The rice yield and total biomass for the five N treatments were found to be significantly different at the 0.05 and 0.1 levels of significance, respectively, and normalized difference vegetation index (NDVI) values at panicle initiation stage were highly correlated with yield and total biomass with regression coefficients (r^2) of 0.728 (RMSE = 0.458 ton ha^{-1}) and 0.760 (RMSE = 0.598 ton ha^{-1}), respectively. The study demonstrated the suitability of using LARS images as a substitute for satellite images for estimating leaf chlorophyll content in terms of NDVI values (r^2 = 0.897, RMSE = 0.012). The LARS system described has potential to evaluate areas that require additional nutrients at critical growth stages to improve final yield in rice cropping.*

Keywords. *Biomass yield, NDVI, Nutrient stress, Remote sensing, Rice yield, Unmanned aerial vehicle, Vegetation index.*

Rice (*Oriza sativa* L.), which is the staple food of most Asian countries, accounts for more than 40% of caloric consumption worldwide (IRRI, 2006). Annual rice production was approximately 590 million tons and yield was 4.21 ton ha^{-1} in Asia for 2006 (FAOSTAT, 2007). The profit from cultivating a rice crop is derived from the crop grain yield and total biomass produced. Predicting rice yield at or around the panicle initiation stage would provide valuable information for future planning and yield expectations. Application of precision agriculture (PA) technology has become increasingly prevalent among the farmers from developed countries as well as developing countries due to its capability for optimizing crop yield by facilitating sound crop status monitoring (Zhang and Taylor, 2001).

Assessment of leaf radiation has the potential to detect nitrogen (N) deficiency and is a promising tool for N management and monitoring. Moreover, fertilizer application in excess of plant needs may result in surface runoff and pollution of water bodies and streams (Wood et al., 1993; Auernhammer et al., 1999; Daughtry et al., 2000). Chlorophyll is an indirect indicator of nitrogen status and is used in optical reflectance-based variable-rate nitrogen application technology (Lee and Searcy, 2000; Jones et al., 2004; Alchanatis et al., 2005; Kim and Reid, 2006; Min et al., 2008). Biermacher et al. (2006) used sensor-based systems to determine crop nitrogen requirements and estimated that the variable-rate system had the potential to achieve a net profit of about $22 to $31 per ha. The ability to accurately estimate plant chlorophyll concentration can provide growers with valuable information to estimate crop yield potential and to make decisions regarding N management (Gamon and Surfus, 1999; Kahabka et al., 2004; Reyniers and Vrindts, 2006).

Spectroradiometry has been useful in the research environment for determining principal wavebands and spectral patterns that relate to nutrient stress (Noh et al., 2004; Tumbo et al. 2001). High spectral resolution and the ability to account for temporal changes are distinct advantages. Okamoto et al. (2007) used a hyperspectral line-scanning camera for weed detection. This system produced hyperspectral images from a Specim ImSpector V9 imaging spectrograph mounted on a tractor that was set to move slowly through the field. Principal spectral components could be extracted and analyzed using various discrimination schemes. However, on-the-go hyperspectral sensing may be difficult for practical use, since enough area must be covered per sweep for timely data acquisition over large field areas.

Prediction of yield using remote sensing images has been practiced by many researchers. Rice crop area has been estimated from Landsat images (Tennakoon et al., 1992) for wide-scale yield prediction. Canopy reflectance was estimated at panicle initiation stage using a portable spectrora-

Submitted for review in December 2008 as manuscript number PM 7841; approved for publication by the Power & Machinery Division of ASABE in February 2010.

Mention of trademark, vendor, or proprietary product does not constitute a guarantee or warranty of the product by The Asian Institute of Technology or the USDA-ARS and does not imply its approval to the exclusion of other products that may also be suitable.

The authors are **Kishore C. Swain,** Research Specialist, and **Hemantha P. W. Jayasuriya, ASABE Member Engineer,** Assistant Professor, Department of Agricultural Systems Engineering, Asian Institute of Technology, Klong Luang, Pathumthani, Thailand; and **Steven J. Thomson, ASABE Member Engineer,** Research Agricultural Engineer, USDA-ARS Crop Production Systems Research Unit, Stoneville, Mississippi. **Corresponding author:** Kishore C. Swain, Department of Agricultural Systems Engineering, Asian Institute of Technology, Klong Luang, Pathumthani, Thailand 12120; phone: +662-524-5453; fax: +662-524-6200; e-mail: swainkc@yahoo.com.

diometer (LI-1800, LICOR) with a remote cosine receptor attached to a 1.5 m extension arm for smaller-scale yield prediction (Chang et al., 2005). Yield prediction has also been accomplished for corn (Chang et al., 2003; Kahabka et al., 2004), cotton (Thomasson et al., 2000), wheat (Doraiswamy et al., 2003), and citrus (Zaman et al., 2006). Tea leaf yield was estimated using vegetation indices such as normalized difference vegetation index (NDVI) and triangular vegetation index (TVI) (Rama Rao et al., 2007). Crop residue estimation has been accomplished using RADARSAT images (Jensen et al., 1990; McNairn et al., 1998), using LANDSAT images (Thoma et al., 2004), and using images captured by radio-controlled model aircraft (Hunt et al., 2005).

The objective of this study is to determine the effectiveness of low-altitude remote sensing (LARS) images obtained by a multispectral imaging platform mounted in a radio-controlled unmanned helicopter to estimate rice yield and total biomass as a function of varying nutrient availability. Consistent with the fact that most multispectral cameras small enough to be used in unmanned aerial vehicles utilize pre-defined wavebands for feature detection, applicability of the widely used NDVI incorporating these wavebands is evaluated.

LARS System

The major constraint in PA adoption is the availability of reliable data. Remote sensing images have many constraints in terms of image quality and resolution, as well as timely availability of the images. Agricultural crops are biological products, very sensitive to the environment and input nutrient levels, which can affect the final outcome in terms of reduced crop yield and/or quality. Therefore, the use of PA technology is gaining momentum for agricultural crops for preventive management. Selective management of inputs characteristic of PA promotes conservation of inputs while maintaining crop viability. However, the application of satellite-based images still cannot fulfill the specific requirements of PA technology. Stafford (2000) observed that images collected from satellites for application to PA are handicapped in terms of spectral and temporal resolution and can be affected by bad weather conditions. Lamb and Brown (2001) indicated that the low-resolution images from satellites, only beneficial for large-scale studies, are not appropriate for the small-scale farms prevalent in many areas of Asia, for example. Additionally, satellites providing higher-resolution images, e.g., QuickBird (DigitalGlobe, Longmont, Colo.) and ASTER (National Aeronautics and Space Administration, Washington, D.C.), have long revisit times, making them of limited utility for any application that might require frequent images (nutrient stress monitoring, for example).

LARS is a relatively new concept of remote image acquisition currently discussed by the agriculturists involved in precision agriculture technology. As the name suggests, it is a system of acquiring images of the earth surface from a lower altitude as compared to the commercial remote sensing satellites. In this system, the images are acquired mostly below cloud cover and very near field features of interest. Low-altitude remote sensing using unmanned aerial vehicles can be an inexpensive and practical substitute for sophisticated satellite and general aviation aircraft, and it is immediately accessible as a tool for the farmer.

Various unmanned LARS systems have been developed and used in the remote image acquisition for PA applications. Some LARS platforms have been kites (Aber et al., 2002), balloons (Amoroso and Arrowsmith, 2000; Seang and Mund, 2006), high-clearance tractors (Bausch and Delgado, 2005), and unmanned airplanes and helicopters (Sugiura et al., 2002; Fukagawa et al., 2003; Eisenbiss, 2004; Herwitz el al., 2004; Sugiura et al., 2004; Hunt et al., 2005; MacArthur et al., 2005, 2006; Xiang and Tian, 2006, 2007a, 2007b; Huang et al., 2008). These platforms were mounted with image acquisition devices and location measuring receivers, which can fly over agriculture farms and targeted areas for capturing images. Thomson and Sullivan (2006) observed that both agricultural aircraft and unmanned aerial vehicles (UAVs) are potentially more easily scheduled and accessible remote sensing platforms than the remote sensing satellites and general aviation aircraft customarily used in the U.S. However, use of agricultural aircraft is limited to those areas where aerial crop spraying is prevalent. Hunt et al. (2005) used a radio-controlled helicopter-mounted image acquisition system to estimate biomass and nitrogen status for corn, alfalfa, and soybean crops. Digital photographs have been used for site-specific weed control for grassland swards (Gebhardt et al., 2006; Beerwinkle, 2001) and for tomato (Zhang et al., 2005). Chen et al. (2003), using an high-elevation tractor system, indicated that multi-spectral images at 555, 660, and 680 nm wavelength band centers demonstrated good prediction ability for determining the nitrogen content of rice plants.

Methodology

Theoretical Calculations

The normalized difference vegetation index (NDVI) (Rouse et al., 1973; Fablo and Felix, 2001; Zhang et al., 2003; Chang et al., 2005) is the most widely adopted vegetation index for agricultural cropping and vegetation studies. Alvaro et al. (2007) used the NDVI and SR (simple ratio) to estimate total biomass for four cereal crops (barley, bread wheat, durum wheat, and triticale). The NDVI is popular because it is robust (Schmaltz, 2005), requires no atmospheric corrections, and reduces the impact of sunlight intensity variations. This index, evaluated herein for its suitability for determining yield and biomass of rice, is defined as:

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \tag{1}$$

where

NIR = spectral reflectance value for the near-infrared band

R = spectral reflectance value for the red band.

Equation 1 was used to estimate the $\text{NDVI}_{\text{Spectro}}$ and $\text{NDVI}_{\text{LARS}}$ values for the spectroradiometer readings and LARS image readings, respectively. Rice yield was estimated at 14% moisture content (MC) for each treatment (Field crop report, 1998):

$$\text{Yield (ton ha}^{-1}) = \frac{(100 - \text{MC}) \times \text{RW} \times 10000}{86 \times \text{A} \times 1000} \tag{2}$$

where

MC = moisture content (% wet basis)

RW = weight of rice (kg)

A = harvested area (m^2).

Field Preparation

In this study, images taken by a LARS system were analyzed to determine their suitability for estimating rice yield and biomass as a function of applied nitrogen. Nitrogen fertilizer was applied at five rates: 0%, 25%, 50%, 75%, and 100% of recommended values, representing 0, 33, 66, 99, and 132 kg ha^{-1}, respectively. Plots with different nitrogen rates were maintained to promote a wide range of rice yield so the effectiveness of LARS images could be evaluated for varying nutrient availability. This follows a similar technique by Chen et al. (2003), who used four N rates (0, 45, 90, and 135 kg ha^{-1}) in field experiments with a Tainung 67 rice crop for multispectral image analysis.

The experimental site was located in Pathumthani Province, Thailand (14° 12′ N, 100° 37′ E). The soil of the experimental site belonged to the clay textural class with a bulk density of 1.38 g cm^{-3} and pH of 4.2. Three replicates were made, and the treatment plots, each of size 10 m × 10 m, were randomly distributed within each replicate. To estimate the nitrogen application rate, the total nitrogen present in the soil was tested using standard methods (Kjeldahl apparatus). It was found that the concentration of pre-existing nitrogen was low (<0.18%) for all the plots, per the local Agricultural Extension Service guidelines. The plots were well-watered using flood irrigation and carefully maintained for pest control to ensure uniform yield potential. The rice seeds were broadcasted (on 14 Dec. 2006) in accordance with local practices under irrigated farming conditions. An early rice variety, Supanburi-1 (95 day period), was used in the study, as this is the most popular variety in central Thailand. Urea (46-0-0) was applied as the source of nitrogen for the study. Different nitrogen rates along with recommended phosphorous fertilizer were applied 30 days after sowing rice.

Equipment

For the study, a remote-controlled model helicopter (X-Cell Fury 91, Miniature Aircraft, Billings, Mont.) was equipped with a Tetracam agricultural digital camera (ADC) (Tetracam, Inc., Chatsworth, Cal.) (table 1). This camera is a wideband multispectral camera utilizing a CMOS CCD (charge-coupled device) with a Bayer filter mask for multispectral imaging. The unmanned helicopter weighed about 6 kg with a payload capacity of 5 kg. The radio console was capable of controlling the unmanned helicopter within a 1 km radius. The system used a battery-initiated glow fuel (250 mL) engine, supporting 15 min of flight. A spectroradiometer with wavelength range of 350 to 2350 nm (Spectra Co-op, Inc., Tokyo, Japan) was used to estimate reflectance at ground level in the red (at 660 nm) and NIR bands (at 800 nm). Bandwidth at each center was 2.5 nm.

Table 1. Specification of the Tetracam ADC green-red-NIR sensors.

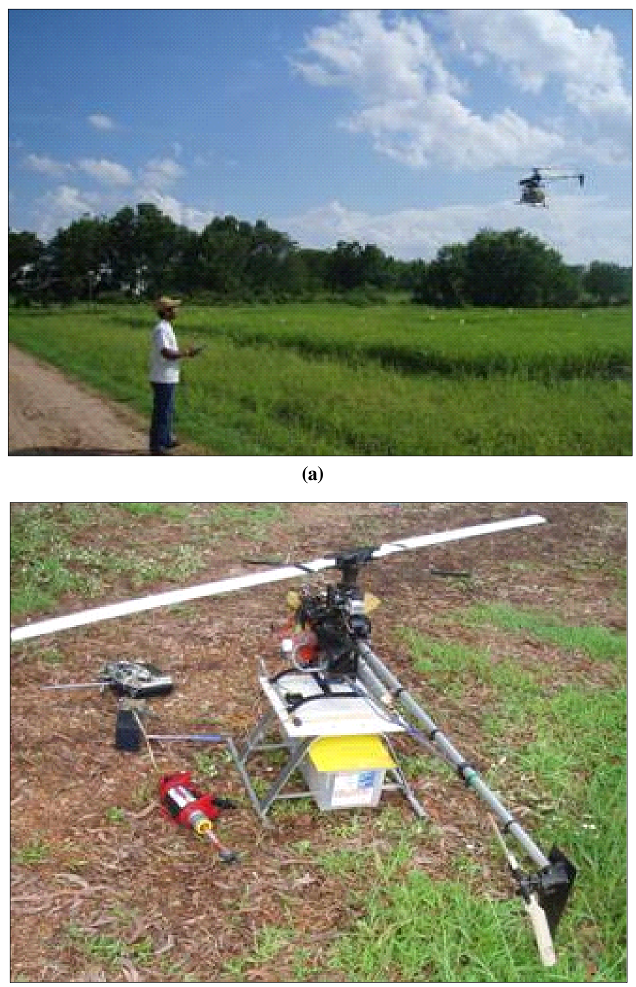
Characteristics	Values
Image size (resolution)	1280 × 1024 (1.3 Mpixel)
Pixel size	6.01 micron
Ground pixel resolution	0.000707 m/pixel (estimated)
Spectral bands	3 (green, red, and NIR); band centers and bandwidths are fundamentally equivalent to Landsat bands TM2, TM3, and TM4
Lens type	C-mounted
Lens	8.5 mm
Triggering	Manual/cable switch triggering

Data Acquisition

Images were obtained with the LARS system just before panicle initiation stage (65 days after planting, fig. 1). Field images were acquired at an altitude of 20 m. This altitude was selected considering the camera's field of view to acquire a single image for each treatment plot. Images with effective dimensions of 18 m × 14 m were collected from a 20 m flying height, covering a single plot. Flight altitude was recorded with a height sensor (MPXAZ4115A barometric sensor, Freescale Semiconductor, Austin, Tex.) mounted on the LARS system. Images were obtained at five different heights, and the images obtained closest to the 20 m height were selected for analysis. Five ground-based reflectance readings were obtained for the rice canopy and $BaSO_4$ standard white reference board using the spectroradiometer in each of the experimental plots. The ground-based readings were obtained immediately after the LARS system-based image acquisition. The plotwise ground-based reflectance value was calculated as the mean of the five readings.

Image Processing

Multispectral images acquired by the Tetracam ADC camera (.dcm format) were converted into .tiff format for analysis. Images were uploaded to Pixelwrench software (Tetracam, Inc., Chatsworth, Cal.), which contains programs for



(a)

(b)

Figure 1. LARS system operation: (a) acquiring image in rice crop, and (b) R/C helicopter mounted with image acquisition system.

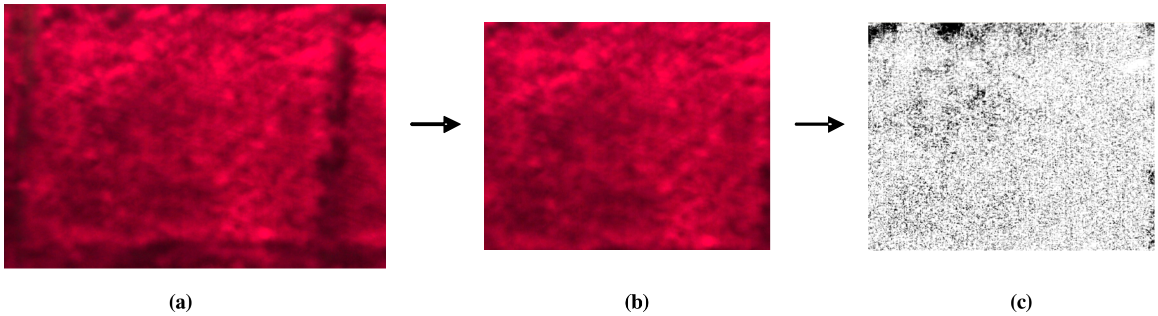


Figure 2. Stages of image processing: (a) raw image with plot boundaries (as taken by the image acquisition system), (b) plot-scale image of the rice crop, and (c) NDVI image of the plot.

deriving one of several vegetation indices (.hdr format) from raw image data. An NDVI image was produced for each test plot, and the average NDVI index was estimated using a custom-developed program in the C programming language from images acquired by the LARS-mounted sensors (fig. 2). Ground-based reflectance data were collected to estimate mean NDVI of the experimental plots ($NDVI_{Spectro}$). $NDVI_{Spectro}$ was estimated using the software provided by the spectroradiometer manufacturer. Linear regression models were developed in SAS (ver. 9.1, SAS Institute, Inc., Cary, N.C.).

Results and Discussion

Statistical Analysis of Data

The rice crop was harvested from three sample areas of 4 m^2 from each plot, 102 days after sowing for this experiment. The moisture content (% w.b.) at the time of weighing was estimated using a field moisture meter (Kett PM600, Ohta-Ku, Tokyo, Japan). The yield of each plot (100 m^2 area) was estimated as the average of three sampled areas and converted to a ton-per-hectare area at 14% moisture content using equation 2. Rice yield ranged from as low as 1.88 ton ha^{-1} (0 kg ha^{-1} N) to 3.68 ton ha^{-1} (132 kg ha^{-1} N) based on a 14% MC, illustrating the effectiveness of the fertilizer treatment rates on rice yield (table 2). Total oven-dried biomass ranged from 3.58 to 7.36 ton ha^{-1} for the different treatments (table 3). The crop yield and biomass dry weights were also tested for statistical significance (Johnson and Bhattacharyya, 2001). Yield data between the treatments showed significant differences at the 0.10 and 0.05 levels, whereas differences were not significant among the replicates (table 4). Total dry biomass weight between the treatments showed significant differences at the 0.10 level but not between replicates (table 5).

Suitability of NDVI in Analysis of LARS Images

The graph of $NDVI_{Spectro}$ and $NDVI_{LARS}$ for the different N treatments indicated good correlation (r^2 = 0.897, RMSE = 0.012) with the increase in recommended nitrogen rates (fig. 3) for all three replicates. The trend indicates the influence of N treatment rate on crop leaf reflectance through leaf chlorophyll content (Lee et al., 2002). The range of $NDVI_{LARS}$ indices showed higher values compared with $NDVI_{Spectro}$ readings. This may have been due to noise caused by reflectance of exposed soil along with rice crop leaves during data collection using the spectroradiometer, although care was taken to minimize these errors in the field.

Table 2. Rice yield (ton ha^{-1}) of the experimental plots.

N Rate Treatment	Replicate 1	Replicate 2	Replicate 3	Average
0 kg ha^{-1}	1.88	1.97	1.64	1.83
33 kg ha^{-1}	2.13	2.87	3.28	2.76
66 kg ha^{-1}	2.78	2.70	3.44	2.97
99 kg ha^{-1}	2.37	3.85	3.52	3.25
132 kg ha^{-1}	3.52	3.36	3.68	3.52

Table 3. Total biomass (ton ha^{-1}) of the experimental plots.

N Rate Treatment	Replicate 1	Replicate 2	Replicate 3	Average
0 kg ha^{-1}	3.58	4.25	6.30	4.710
33 kg ha^{-1}	5.51	5.84	5.64	5.660
66 kg ha^{-1}	5.57	5.97	5.77	5.771
99 kg ha^{-1}	6.50	7.36	5.97	6.611
132 kg ha^{-1}	5.57	6.63	7.30	6.501

Table 4. Randomized block ANOVA analysis table for rice yield.

Source	Sum of Squares	df	Mean Square	F-Ratio (estimate)	F-tabulated α = 0.05	F-tabulated α = 0.10
Treatment	5.030	4	1.2576	7.006**	3.84	2.81
Replicate	0.873	2	0.4365	2.432	4.46	3.11
Residual	1.436	8	0.179			

** = Significant at the 0.05 level.

Table 5. Randomized block ANOVA analysis table for total biomass.

Source	Sum of Squares	df	Mean Square	F-Ratio	F-tabulated α = 0.05	F-tabulated α = 0.10
Treatment	7.036	4	1.759	3.015*	3.84	2.81
Replicate	1.992	2	0.996	1.708	4.46	3.11
Residual	4.667	8	0.583			

* = Significant at the 0.10 level.

Estimation of Rice Yield Using $NDVI_{LARS}$ Index

The regression model developed for rice yield with NDVI index value in SAS 9.1 indicated a good fit (r^2 = 0.728, RMSE = 0.458 ton ha^{-1}, fig. 4). Variation among the replicates might be due to initial nutrient levels present in the soil from randomly selected plots.

Estimation of Total Biomass from $NDVI_{LARS}$ Index

The plot-wide total biomass weight of rice crop was determined for N treatments in each replicate, and then converted

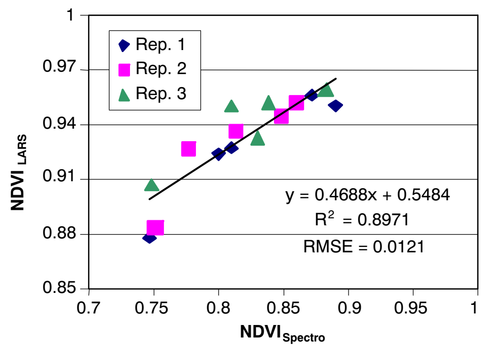


Figure 3. Variation of NDVI values measured from spectroradiometer reading and LARS images for different N treatments. Each of the five points represents a different rate of applied N.

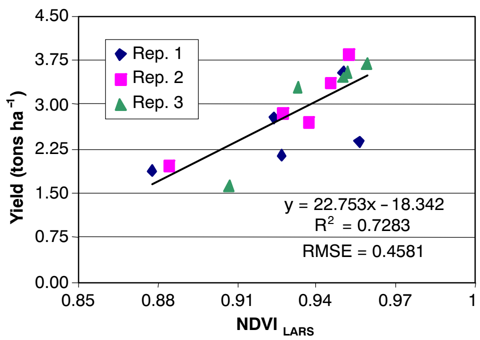


Figure 4. Estimation of rice yield with $NDVI_{LARS}$ values.

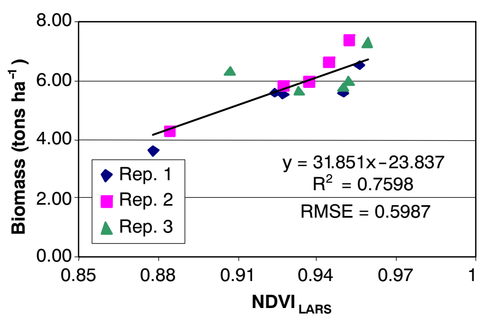


Figure 5. Estimation of biomass with $NDVI_{LARS}$ values.

to a per-hectare basis. Linear calibrations were developed in SAS to estimate the biomass from NDVI index values calculated from LARS images. From these results, $NDVI_{LARS}$ could explain 76% of the variation in biomass weight (r^2 = 0.760, RMSE = 0.598 ton ha^{-1}, fig. 5).

System Cost Estimates

For feasibility and practical use of a system like this, it may be instructive to provide an estimate of both system costs and operating costs. Total cost of the system was $15,000 USD, which included the major components: unmanned helicopter, landing skid, ADC camera, microprocessor and GPS receiver, magnetic compass, IMU, and altitude sensors. Assuming the same figures for other agricultural equipment can be used, 10% of the total cost can be allotted for repair and maintenance (Wahby and Al-Suhaibani, 2001; Rotz and Bowers, 1991). An additional 10% of total cost is also allotted for miscellaneous expenditures associated with the system. Therefore:

$$\begin{aligned}\text{Total cost} &= \$15{,}000\ \text{USD}\\ &\quad + (0.10 \times \$15{,}000\ \text{USD})\\ &\quad + (0.10 \times \$15{,}000\ \text{USD})\\ &= \$18{,}000\ \text{USD}\end{aligned}$$

The initial cost of a LARS is quite low, but data analysis and image interpretation costs should also be considered. Costs for a system like this could be well within reach of farmers in developing countries if they pool their resources (form a cooperative). Countries with larger farmed areas could also benefit from use of unmanned aerial systems if high-resolution cameras are used and radio frequency (RF) range is extended to allow higher-altitude flight over large field areas.

Summary and Conclusions

A radio-controlled helicopter-based LARS system was used to acquire multispectral images over a rice canopy to estimate rice yield. The study indicated that the LARS platform could substitute for satellite-based and costly airborne remote sensing methods for estimation of yield and biomass as a function of nutrient status for rice, a staple crop in developing countries. Images were be obtained successfully by the multispectral camera mounted on a radio-controlled helicopter at a height of 20 m over rice plots. Rice yield and total biomass were found to be significantly different at the 0.05 and 0.1 significance levels, respectively, under different N treatment regimes. The relationship between $NDVI_{LARS}$ and $NDVI_{Spectro}$ (r^2 = 0.897, RMSE = 0.012) indicated the applicability of LARS sensor-based images for estimating NDVI values, which varied over the five levels of applied N. A linear regression model showed a good fit (r^2 = 0.728, RMSE = 0.458 ton ha^{-1}) for estimating total biomass for rice using LARS image-based NDVI values. A linear model (r^2 = 0.760, RMSE = 0.598 ton ha^{-1}) indicated that rice yield could be predicted with NDVI values derived from LARS images.

Modeled yield projections can evaluate areas that require additional nutrients at critical growth stages to improve final yield in rice cropping. This study could be extended further for different rice varieties along with nitrogen treatment rates. The regression model procedure outlined herein can be followed for larger rice fields by recording crop input rates and acquiring LARS images. The rice variety (Supanburi-1) is a three-month crop with harvesting time that varies between 95 and 110 days. Imaging with the LARS system was accomplished at panicle initiation stage, i.e., 65 days of sowing.

Yield variation maps can be developed for the entire field well before the rice crop is harvested. Such maps could provide specific information about the expected rice yield pattern from the field. Furthermore, low-yielding areas could be identified and remedial treatments, such as additional nutrient (N), could be applied. The time window normally available for crop scouting of yield-restricting factors and application of preventive measures is very limited. A low-cost LARS system would be well-suited for quick image acquisition and data analysis for proper assessment of crop growth. Good correlation between biomass and image data were also indicated in this study. Rice straw has been used as a major cattle feed (Abdulla et al., 1992; Kennedy, 1995) in various parts of the world. The information could assist in assessing the amount of biomass expected from the rice crop well in advance (one month before harvesting).

References

Abdullah, N., Y. W. Ho, and S. Jalaludin. 1992. Microbial colonization and digestion of feed materials in cattle and buffaloes: II. Rice straw and palm press fibre. *Asian-Australasian J. Animal Sci.* 5(2): 329-335.

Aber, J. S., K. Aaviksoo, E. Karofeld, and S. W. Aber. 2002. Patterns in Estonian bogs as depicted in color kite aerial photographs. *Suo (Mires and Peat)* 53(1): 1-15.

Alchanatis, V., Z. Schmilovitch, and M. Meron. 2005. In-field assessment of single-leaf nitrogen status by spectral reflectance measurements. *Precision Agric.* 6(1): 25-39.

Alvaro, F., L. F. García del Moral, and C. Royo. 2007. Usefulness of remote sensing for the assessment of growth traits in individual cereal plants grown in the field. *Intl. J. Remote Sensing* 28(11): 2497-2512.

Amoroso, L., and R. Arrowsmith. 2000. Balloon photography of brush fire scars east of Carefree, Arizona. Tempe, Ariz.: Arizona State University, Department of Geological Sciences. Available at: http://activetectonics.asu.edu/Fires_and_Floods/10_24_00_photos.

Auernhammer, H., M. Demmel, F. X. Maidl, U. Shmidnalter, T. Schneider, and P. Wagner. 1999. An on-farm communication system for precision farming with nitrogen real-time application. ASAE Paper No. 991150. St. Joseph, Mich.: ASAE.

Bausch, W., and J. A. Delgado. 2005. Impact of residual soil nitrate on in-season nitrogen applications to irrigated corn based on remotely sensed assessments of crop nitrogen status. *Precision Agric.* 6(6): 509-519.

Beerwinkle, K. R. 2001. An automatic capture-detection, time-logging instrumentation system for boll weevil pheromone traps. *Applied Eng. in Agric*. 17(6): 893-898.

Biermacher, J. T., F. M. Epplin, B. W. Brorsen, J. B. Solie, and W. R. Raun. 2006. Maximum benefit of a precise nitrogen application system for wheat. *Precision Agric*. 7(3): 193-204.

Chang, J., D. E. Clay, K. Dalsted, S. Clay, and M. O'Neill. 2003. Corn (*Zea mays* L.) yield prediction using multispectral and multidate reflectance. *Agron. J.* 95(6): 1447-1453.

Chang, K. W., Y. Shen, and J. C. Lo. 2005. Predicting rice yield using canopy reflectance measured at booting stage. *Agron. J*. 97(3): 872-878.

Chen, S., C. W. Huang, C. C. Huang, C. K. Yang, T. H Wu, Y. Z. Tsai, and P. L. Miao. 2003. Determination of nitrogen content in rice crop using multi-spectral imaging. ASAE Paper No. 031132. St. Joseph, Mich.: ASAE.

Daughtry, C. S. T., C. L. Walthall, M. S. Kim, E. B. de Colstoun, and J. E. McMurtrey III. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sensing of Environ.* 74(2): 229-23.

Doraiswamy, P. C., S. Moulin, P. W. Cook, and A. Stern. 2003. Crop yield assessment from remote sensing. *Photogram. Eng. and Remote Sensing* 69(6): 665-674.

Eisenbiss, H. 2004. A mini unmanned aerial vehicle (UAV): System overview and image acquisition. In *Proc. Intl. Workshop on Processing and Visualization Using High-Resolution Imagery.* International Society for Photogrammetry and Remote Sensing (ISPRS).

Fablo, M., and R. Felix. 2001. Analysis of GAC NDVI data for cropland identification and yield forecasting in Mediterranean African countries. *Photogram. Eng. and Remote Sensing* 67(5): 593-602.

FAOSTAT. 2007. *Agricultural Statistics Yearbook: 2006*. Rome, Italy: Food and Agriculture Organization of the United Nations.

Field crop report. 1998. Field crop report for rice cropping in Thailand. Bangkok, Thailand: Field Crop Research Station.

Fukagawa, T., K. Ishii, N. Noguchi, and H. Terao. 2003. Detecting crop growth by a multispectral imaging sensor. ASAE Paper No. 033125. St. Joseph, Mich.: ASAE.

Gamon, J. A., and J. S. Surfus. 1999. Assessing leaf pigment content and activity with a reflectometer. *New Phytologist* 143(1): 105-117.

Gebhardt, S., J. Schellberg, R. Lock, and W. Kuhbauch. 2006. Identification of broad-leaved dock (*Rumex obtusifolius* L.) on grassland by means of digital image processing. *Precision Agric.* 7(3): 165-178.

Herwitz, S. R., L. F. Johnson, S. E. Dunagan, and R. G. Higgins. 2004. Imaging from an unmanned aerial vehicle: Agricultural surveillance and decision support. *Computers and Electronics in Agric.* 44(1): 49-61.

Huang, Y., Y. Lan, W. C. Hoffmann, and B. Fritz. 2008. Development of an unmanned aerial vehicle-based remote sensing system for site-specific management in precision agriculture. In *Proc. 9th Intl. Conf. on Precision Agriculture.* Denver, Colo.: Colorado State University.

Hunt, E. R., C. L. Walthall, and C. S. T. Daughtry. 2005. High-resolution multispectral digital photography using unmanned airborne vehicles. In *Proc. 20th Biennial Workshop on Aerial Photography, Videography, and High-Resolution Digital Imagery for Resource Assessment.* Bethesda, Md.: American Society for Photogrammetry and Remote Sensing (ASPRS).

IRRI. 2006. *Atlas of Rice and World Rice Statistics.* Manila, Philippines: International Rice Research Institute.

Jensen, A., B. Lorenzen, H. Spelling-Ostergaard, and E. Kloster-Hvelplund. 1990. Radiometric estimation of biomass and N content of barley grown at different N levels. *Intl. J. Remote Sensing* 11(10): 1809-1820.

Johnson, R. A., and G. K. Bhattacharyya. 2001. *Statistics: Principles and Methods.* 4th ed. John Wiley and Sons.

Jones, C. L., N. O. Maness, M. L. Stone, and R. Jayasekara. 2004. Chlorophyll estimation using multi-spectral reflectance and height sensing. ASAE/CSAE Paper No. 043081. St. Joseph, Mich.: ASAE.

Kahabka, J. E., H. M. V. Es, E. J. McClenahan, and W. J. Cox. 2004. Spatial analysis of maize response to nitrogen fertilizer in central New York. *Precision Agric.* 5(5): 463-476.

Kennedy, P. M. 1995. Intake and digestion in swamp buffaloes and cattle: 3. Comparison with four forage diets, and with rice straw supplemented with energy and protein. *J. Agric. Sci. Cambridge* 124(2): 265-275.

Kim, Y., and J. F. Reid. 2006. Modeling and calibration of a multi-spectral imaging sensor for in-field crop nitrogen assessment. *Applied Eng. in Agric*. 22(6): 935-941.

Lamb, D. W., and R. B. Brown. 2001. Remote sensing and mapping of weeds in crops. *J. Agric. Eng. Res.* 78(2): 117-125.

Lee, W. S., and S. Searcy. 2000. Multispectral sensor for detecting nitrogen in corn plants. ASAE Paper No. 001010. St. Joseph, Mich.: ASAE.

Lee, Y. S., C. M. Yang, and A. H. Chang. 2002. Changes of nitrogen and chlorophyll contents and reflectance spectral characteristics to the application of nitrogen fertilizer in rice plants. *J. Agric. Res. China* 51(1): 1-14.

MacArthur, D., J. K. Schueller, and C. D. Crane. 2005. Remotely piloted mini-helicopter imaging of citrus. ASAE Paper No. 051055. St. Joseph, Mich.: ASABE.

MacArthur, D., J. K. Schueller, W. S. Lee, C. D. Crane, E. Z. MacArthur, and L. R. Parsons. 2006. Remotely piloted helicopter citrus yield map estimation. ASABE Paper No. 063096. St. Joseph, Mich.: ASABE.

McNairn, H., D. Wood, Q. H. J. Gwyn, R. J. Brown, and F. Charbonneau. 1998. Mapping tillage and crop residue management practices with RADARSAT. *Canadian J. Remote Sensing* 24(1): 110-115.

Min, M., W. S. Lee, T. F. Burks, J. D. Jordan, A. W. Schumann, J. K. Schueller, and H. Xie. 2008. Design of a hyperspectral nitrogen sensing system for orange leaves. *Computers and Electronics in Agric*. 63(2): 215-226.

Noh, H. K., Q. Zhang, and S. Han. 2004. Sensor-based variable-rate application of nitrogen by using multi-spectral image sensor. ASAE Paper No. 041133. St. Joseph, Mich.: ASAE.

Okamoto, H., T. Murata, T. Kataoka, and S-I Hata. 2007. Plant classification for weed detection using hyperspectral imaging with wavelet analysis. *Weed Biol. and Mgmt*. 7(1): 31-37.

Rama Rao, N., M. Kapoor, N. Sharma, and K. Venkateswarlu. 2007. Yield prediction and waterlogging assessment for tea plantation land using satellite image-based techniques. *Intl. J. Remote Sensing* 28(7): 1561-1576.

Reyniers, M., and E. Vrindts. 2006. Measuring wheat nitrogen status from space and ground-based platform. *Intl. J. Remote Sensing* 27(3): 549-567.

Rotz, C. A., and W. Bowers. 1991. Repair and maintenance cost data for agricultural equipment. ASAE Paper No. 911531. St. Joseph, Mich.: ASAE.

Rouse, J. W., R. H. Haas, J. A. Shell, and D. W. Deering. 1973. Monitoring vegetation systems in the Great Plains with ERTS-1. In *Proc. 3rd Earth Resources Technology Satellite Symp.*, 1: 309-317. NASA SP-351. Washington, D.C.: NASA.

Schmaltz, J. 2005. Visible Earth: A catalog of NASA images and animations of our home planet. Washington, D.C.: NASA. Available at: http://visibleearth.nasa.gov/view_rec.php?id=8325.

Seang, T. P., and J.-P. Mund. 2006. Geo-referenced balloon digital aerial photo technique: A low-cost high-resolution option for developing countries. In *Proc. Map Asia 2006: 5th Annual Conf. on Geographic Information Technology and Application*. Noida, India: GIS Development Pvt. Ltd.

Stafford, J. V. 2000. Implementing precision agriculture in the 21st century. *J. Agric. Eng. Res.* 76(3): 267-275.

Sugiura, R., N. Noguchi, K. Ishii, and H. Terao. 2002. The development of remote sensing system using unmanned helicopter. In *Proc. Automation Technology for Off-Road Equipment*, 120-128. ASAE Paper No. 701P0502. Q. Zhang, ed. St. Joseph, Mich.: ASAE.

Sugiura, R., K. Ishii, and N. Noguchi. 2004. Remote sensing technology for field information using an unmanned helicopter. In *Proc. Automation Technology for Off-Road Equipment*. ASAE Paper No. 701P1004. St. Joseph, Mich.: ASAE.

Tennakoon, S. B., V. V. N. Murty, and A. Eiumnoh. 1992. Estimation of cropped area and grain yield of rice using remote sensing data. *Intl. J. Remote Sensing* 13(3): 427-439.

Thoma, D., S. Gupta, and M. Bauer. 2004. Evaluation of optical remote sensing models for crop residue cover assessment. *J. Soil and Water Cons. Soc.* 59(5): 224-233.

Thomasson, J. A., R. Sui, and D. C. Akins. 2000. Spectral changes in picked cotton leaves with time. In *Proc. 5th Intl. Conf. on Precision Agriculture and Other Precisions Resources Mgmt.* Madison, Wisc.: ASA.

Thomson, S. J., and D. G. Sullivan. 2006. Crop status monitoring using multispectral and thermal imaging systems for accessible aerial platforms. ASABE Paper No. 061179. St. Joseph, Mich.: ASABE.

Tumbo, S. D., D. G. Wagner, and P. H. Heinemann. 2001. On-the-go sensing of chlorophyll status in corn. ASAE Paper No. 011175. St. Joseph, Mich.: ASAE.

Wahby, M. F., and S. A. Al-Suhaibani. 2001. Repair and maintenance cost models for agricultural equipment in Saudi Arabia. ASAE Paper No. 011027. St. Joseph, Mich.: ASAE.

Wood, C. W., D. W. Reeves, and D. G. Himelrick. 1993. Relationships between chlorophyll meter readings and leaf chlorophyll concentration, N status, and crop yield: A review. *Proc Agron. Soc. New Zealand* 23: 1-9.

Xiang, H., and L. Tian. 2006. Development of autonomous unmanned helicopter-based agricultural remote sensing system. ASABE Paper No. 063097. St. Joseph, Mich.: ASABE.

Xiang, H., and L. Tian. 2007a. An autonomous helicopter system for aerial image collection. ASABE Paper No. 071136. St. Joseph, Mich.: ASABE.

Xiang, H., and L. Tian. 2007b. Autonomous aerial image georeferencing for an UAV-based data collection platform using integrated navigation system. ASABE Paper No. 073046. St. Joseph, Mich.: ASABE.

Zaman, Q., A. W. Schumann, and K. H. Hostler. 2006. Estimation of citrus fruit yield using ultrasonically sensed tree size. *Applied Eng. in Agric.* 22(1): 39-44.

Zhang, F., B. Wu, and C. Liu. 2003. Using time series of SPOT VGT NDVI for yield forecasting. In *Proc. Geoscience and Remote Sensing Symp.*, 1: 386-388. Piscataway, N.J.: IEEE.

Zhang, M., Z. Qin, and X. Liu. 2005. Remote sensed spectral imagery to detect late blight in field tomatoes. *Precision Agric.* 6(6): 489-508.

Zhang, N., and R. K. Taylor. 2001. Applications of a field-level geographic information system (FIS) in precision agriculture. *Applied Eng. in Agric.* 17(6): 885-892.